Use and misuse of information in supply chain forecasting of promotion effects

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Abstract:

Demand forecasting is critical to sales and operations planning (S&OP), but the effects of sales promotions can be difficult to forecast. Typically, a baseline statistical forecast is judgmentally adjusted on receipt of information from different departments. However, much of this information either has no predictive value or its value is unknown. Research into base rate discounting has suggested that such information may distract forecasters from the average uplift and reduce accuracy. This has been investigated in situations in which forecasters were able to adjust the statistical forecasts for promotions via a forecasting support system (FSS). In two ecologically valid experiments, forecasters were provided with the mean level of promotion uplift, a baseline statistical forecast, and quantitative and qualitative information. However, the forecasters were distracted from the base rate and misinterpreted the information available to them. These findings have important implications for the design of organizational S&OP processes, and for the implementation of FSSs.

Key Words: Sales and Operations Planning; behavioral operations; information effects; forecaster behavior; judgmental forecasting

1. Introduction

Production and inventory planning, scheduling, logistics, marketing and finance in supply chain companies all rely on short-term disaggregate forecasts at the SKU level. However, little research has been carried out into the way in which such forecasts are actually produced, or the factors that influence their effectiveness (Thomé, Scavarda, Fernandez, & Scavarda, 2012; Tuomikangas & Kaipia, 2014; Seifert, Siemsen, Hadida, & Eisingerich, 2015). In contrast to the academic research literature, the practitioner literature is awash with descriptions and recommendations of ways in which 'Sales and Operations Planning (S&OP)' processes can be used to effectively integrate cross-functional information in order to produce forecasts (e.g., Lapide, 2007; Stahl, 2010). The demand uplifts achieved through sales promotions campaigns can be particularly difficult to forecast because of the relative infrequency of such events. When promotion campaigns are due to take place, the forecasts within S&OP are usually produced as a combination of a simple baseline statistical forecast and a judgmental adjustment, which is an estimate of the promotion effect (Fildes & Goodwin, 2007). The adjustments are made so as to reflect the information received from different departments, such as sales and marketing. These adjustments may mirror individual and functional biases that stemming from informational blind spots, as well as from other organizational misalignments in supply chain processes (Oliva & Watson, 2009, 2011).

In one of the few detailed case studies of forecasting practice, Goodwin, Lee, Fildes, Nikolopoulos, and Lawrence (2007) found that the benefits of judgmental adjustments based on additional information within a pharmaceutical company were slight and often negative. Other studies have found evidence of information use being inefficient and biased (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009; Franses & Legerstee, 2010, 2011, 2013), meaning that adjustments can have a deleterious effect on the forecast accuracy where promotions are concerned (Trapero, Pedregal, Fildes, & Kourentzes, 2013). While the consensus is that integrating diverse sources of information is valuable (Kremer, Siemsen, & Thomas, 2016) and that forecast information sharing affects supply chain performance, usually to improve it (e.g.,

Özer and Raz, 2011; Özer, Zheng, & Chen, 2011), no studies have examined either the nature of the information that was available or the way in which it was used.

One possible cause of damaging judgmental adjustments may be that too much attention is paid to information relating to single, isolated past events, such as one past promotion. Because the effects of such events are subject to noise, they offer little or no diagnosticity[1] when forecasting the effects of similar future events. A second possible cause may be that information with an unknown diagnosticity is overweighted when the judgmental adjustment is estimated. For example, a sales uplift of 80% may be estimated when a top celebrity is recruited to front an advertising campaign for a product, but there may be no information available to support such a judgment, with its typical effects being unknown. The attention that is paid to these two types of information may lead to the neglect of available base rate information, which may indicate, for example, that promotions in the relevant product group or category lead to an average uplift of 50% (e.g. Kahneman & Tversky, 1973).

Using controlled experimentation with realistic simulations of the supply chain forecaster's task environment when sales promotions are imminent, this paper aims to help address the gap in our knowledge of how information is used for forecasting. (Note that the term 'supply chain forecaster' refers to a demand forecaster who is based in a company that forms part of a supply chain that includes both retailers and manufacturers.) It does this by identifying the response of supply-chain-based forecasters when they have base rate information that indicates the average sales uplift achieved during sales promotions, together with other information that has little or unknown diagnosticity – a situation that is common in S&OP settings. Promotions were shown by Fildes and Goodwin (2007) to be the most important reason for judgmental adjustments of demand forecasts, and they are used in this study as an integral part of providing an ecologically valid supply chain forecasting task.

Our research makes three important contributions to the literature. First, it addresses a gap in our knowledge of the ways in which diverse information is used by judgmental forecasters when predicting

[1] "The diagnosticity of a piece of information is a measure of its helpfulness and usefulness for making a judgment (or forecast) in empirical studies" (Qiu, Pang, & Lim, 2012).

the effects of sales promotions in the typical organizational context of a forecasting support system. Other researchers have investigated information use – and, specifically, the role of irrelevant information – in decision making in other, quite different contexts. For example, Gaeth and Shanteau (1984) examined the appraisal of soil types and learning effects when irrelevant materials were contained in soil. The participants in a study by Hutchinson and Alba (1991) attempted a visual product classification task when only one of a collection of pieces of information had diagnosticity. Returning to the classic Kahneman–Tversky experiment regarding the classification of an individual as either an engineer or lawyer, Schwarz, Strack, Hilton, and Naderer (1991) focused on the effects of task framing on the neglect of base rates. Shelton (1999) examined auditor judgments and the effects of experience on individuals' abilities to discount irrelevant information. These and various other studies cited elsewhere in the text all emphasize the effects of irrelevant information; however, the tasks that they have focused on are all far removed from the day-to-day operational tasks faced by demand forecasters. Human judgment depends strongly on the context and nature of the task, so the findings of these studies may not apply when it comes to the important task of demand forecasting in a supply chain. Second, this study investigates how the well-known base rate neglect phenomenon applies to judgmental time series forecasting. Expanding on this, given that we have both qualitative and quantitative information available, we investigate how these different types of information are (mis)weighted. Third, the study is designed to investigate whether there is a tendency to underestimate the effects of special events when adjusting statistical forecasts within a forecasting support system. Such an underestimation might result from a tendency to anchor on the statistical forecasts. Taken together, the findings have important implications for a 'value-added' analysis, where the adjustments made through the organizational S&OP process are evaluated as to their effectiveness in improving the forecasting accuracy.

The paper is divided into five further sections. Following a review of the relevant literature in Section 2, we set out our hypotheses. Section 3 describes our methodology, the participants and the experimental setting. The fourth and fifth sections contain the detailed results of two experiments, with

associated discussion. Finally, Section 6 summarizes our conclusions, as well as providing suggestions for further work and implications for practice.

2. Literature review and hypothesis development

2.1. Base rate distractors

Previous work has acknowledged the importance of using an expanded information set in order to enhance supply chain forecasting performances. Such information may come from both internal sources such as marketing and operations (Fildes & Hastings, 1994), and other supply chain partners (e.g., Eksoz, Mansouri, & Bourlakis, 2014; Önkal & Aktas, 2011). Such an extended information set has been shown to be valuable in enhancing the accuracy, with consequent stock service level improvements (Cui, Allon, Bassamboo, & Mieghem, 2015; Trapero et al., 2013). However, there appears to have been surprisingly little empirical work done on the actual *use* of information in supply chain forecasting, particularly in the important case of sales promotions. When determining the extent to which a baseline statistical forecast should be adjusted to take into account the effect of a forthcoming sales promotion, forecasters will usually have access to a diverse range of information, both quantitative and qualitative. In addition to a base rate figure that shows the average sales uplift achieved by past promotion campaigns, this will typically include historic demand data, past and current baseline statistical forecasts, quantitative information on the most recent sales promotion, and qualitative information on various factors that are judged to be relevant to the success of the forthcoming promotion.

However, one potential problem is that some of this information will have little or no predictive value; that is, no diagnosticity. For example, while a base rate founded on a large sample of previous promotions is likely to provide a reliable estimate of the typical sales uplift, the uplift achieved in the most recent promotion is a sample of only one observation. Using the base rate and the most recent uplift to forecast the uplift of a future promotion is essentially a Bayesian task of combining a prior mean uplift (the base rate) with the evidence from the sample of one to produce a posterior mean. This requires the use of the following formula (assuming that the actual uplifts are normally distributed):

$$m'' = \frac{\sigma^2 m' + n\sigma'^2 m}{n\sigma'^2 + \sigma^2} \ ,$$

where m'' is the posterior mean;

m' is the prior mean;

m is the observed sample mean (in this case, the observed past promotion, as the sample is of size one);

o^2 is the variance of the prior distribution;

σ'^2 is the sample variance (which is undefined, given that we have a sample of size one); and

n is the sample size.

If σ^2 is not known to forecasters, the mean promotion uplift cannot be updated optimally based on this single observation, since σ'^2 is undefined (unless the forecaster assigns a subjective variance estimate to the single observation). Thus, the optimal forecasting strategy is to estimate an uplifted value that is close to the prior, if not identical. Despite this, there is evidence that it is mostly this latest uplift that gets used in promotion forecasting in practice (Cooper, Baron, Levy, Swisher, & Gogos, 1999). Recent observations tend to be more salient (Hutchinson & Alba, 1991), and several other judgmental forecasting studies have found a tendency to focus on them – and particularly on the most recent observation – rather than on the underlying performance of the system that produced them (e.g., Andreassen & Kraus, 1990; Lawrence & O'Connor, 1992, 1995; Bolger & Harvey, 1993).

However, the tendency to use the previous promotion effect in the adjustment to the statistical forecast, thereby neglecting the base rate, is likely to depend on the salience of this effect. Goodwin and Fildes (1999) found that previous promotion effects had no influence on judgmental time series forecasts for promotion periods when the time series were highly noisy. Under these conditions, the previous effects were submerged in the large random movements of the series, and hence were not salient. In contrast, given the prevalence of a recency bias in judgmental forecasting, it seems likely that the proximity of the latest promotion to the current period will increase its salience, hence amplifying its influence on the forecast.

A second problem is that some information, such as an announcement that a particular celebrity has been recruited to lead a promotion campaign, *may* be associated with an uplift in sales, but in the absence of relevant data, the probable size of this effect is unknown, and may even be zero. In these and similar circumstances, the safest strategy is to adjust the statistical baseline forecast by estimating an uplift that is equivalent to the base rate. After all, some of the promotions that were used to estimate the base rate may also have employed celebrities (or had other characteristics that are similar to the forthcoming promotion), though information that would establish this is unlikely to be accessible immediately. Deviating from the base rate in such cases relies implicitly on the unsupported assumption that the celebrity effect (or the effect of any similar characteristic of the promotion that is being forecast) is not already embedded in the base rate. However, information in a narrative form is always likely to act as a powerful distractor from the base rate, even though its diagnosticity is unknown (Önkal, Sayım, & Gönül, 2013). For example, in a classic study of judgmental decision-making, Tversky and Kahneman (1974) showed that information on statistical base rates is often neglected or discounted, with unreliable narrative information being preferred. Kahneman and Lovallo's (1993) notion of the 'inside view' also suggests that the availability of a set of reasons as to why a promotion will or will not be a success will cause attention to be devoted to the specific characteristics of the particular promotion that is being forecast. As a result, the focus on average sales uplifts (the 'outside view') will be lost. The above discussion suggests the following hypothesis:

H1: Adjustments to statistical baseline forecasts in order to take into account forthcoming promotion effects will deviate from base rates when information with no, or unknown, diagnosticity is provided.

How might a focus on the most recent promotion be translated into an adjusted forecast? One possibility is for people to employ the anchor-and-adjust heuristic (Bolger & Harvey, 1993; Epley & Gilovich, 2006; Lawrence & O'Connor, 1995; Tversky & Kahneman, 1974), with the statistical baseline forecast acting as an anchor. This would lead to the forecast being formed as a weighted average of the

baseline statistical forecast and the previous promotion, resulting in a forecast that fell between the two values, and leading, on average, to an underestimate of the promotion effect. Ironically, the use of a weighted average implies that higher statistical forecasts lead to smaller *percentage* adjustments, because in such cases the statistical forecast will be closer to the uplifted sales achieved in the previous promotion. An alternative suggested by de Baets and Harvey (2018) is to use a weighted average of the estimated series mean and the statistical forecast as an initial anchor. Clearly, the presence of sales uplifts reflecting multiple past promotions would be expected to have a significant upward effect on the estimated series mean, compared to cases where only a single past promotion is observed. Nevertheless, their study also found a tendency to under-adjust from this anchor, and hence, typically, to underestimate promotion effects when multiple past promotions were observed.

In addition, when a forecaster has access to multiple items of qualitative information, of which some are positive (suggesting that the promotion will be a relative success) and some are negative (suggesting the contrary), there is some evidence to suggest that the negative information may be more potent (Rozin & Royzman, 2001). This is consistent with Prospect Theory, which assumes that people have an aversion to losses (Kahneman & Tversky, 1979), and hence may be more vigilant in their response to negative information that indicates a potential loss than they would be to positive information. The reasons for the greater influence of negative information are complex, but researchers such as Peeters and Czapinski (1990) have suggested that though negative events are rarer in many environments, they can have more important implications for survival, meaning that it pays to be especially watchful for dangerous negative events. In our context, this negativity bias implies that there may be a tendency to underestimate future promotion effects in situations where positive and negative reasons are equally likely to be present and their diagnosticity is unknown. These factors lead to the following hypothesis:

H2: Adjustments made to statistical baseline forecasts in order to take into account the effects of forthcoming promotions will tend to underestimate these effects when information with no, or unknown, diagnosticity is provided.

In summary, when information relating to a forthcoming promotion is provided as part of the S&OP forecasting process, whether in quantitative, graphical or qualitative forms, the literature suggests that information with zero or unknown diagnosticity is likely to distract a demand forecaster from the normative base rate for promotional events.

2.2. Moderating factors

In practical contexts, there are a number of other factors that may moderate the extent to which both the latest promotion and qualitative information arising from S&OP discussions lead to a tendency to under-forecast future promotion effects (de Baets, 2017). Before commencing the forecasting task, forecasters may have a prior view of the probable impact of promotions based on their (potentially imperfect) recall of earlier promotions (Reimers & Harvey, 2011), their own experiences, or industry beliefs. This may also serve to reduce the weight that is attached to the base rate. Secondly, forecasters in organizations may be subject to motivating factors that cause them to bias their forecasts, whether consciously or unconsciously. The forecaster's motivation may also affect the way in which sets of information in verbal statements will be assessed and aggregated for forecasting (Eroglu & Croxton, 2010). In some situations, forecasters may prefer the variable being forecast to take on high or low values (e.g., a desire for high sales). Such a desirability of outcomes may lead to an overblown optimism that is referred to as a 'desirability bias' (e.g., Windschitl, Smith, Rose, & Krizan, 2010). As Oliva and Watson's (2009) case study shows, such a bias is a common feature of the S&OP forecasting process.

Despite these potential biases, forecasters in organizations are also likely to be motivated to produce accurate forecasts. Indeed, supply chain forecasters identified accuracy as their most important objective in Fildes and Goodwin's (2007) survey. Moreover, prestige and reputational concerns and the knowledge that one's forecast will be evaluated may lead to a 'reality constraint', potentially tempering

factors that may favor biased forecasts, whether overly optimistic or overly pessimistic (Lerner & Tetlock, 1999).

In addition to motivational influences, forecasters all come to the task with relevant past experience, which may affect the weightings that they give to the different pieces of information with which they are presented, whether in a real S&OP process or a simulated process. This has been observed before with auditors (Shelton, 1999), while, in demand forecasting, Franses (2014) found that more experienced forecasters in a pharmaceutical company produced more accurate adjustments.

Finally, the most recent sales figure (as opposed to sales in the most recent promotion period) and the most recent forecast error may have an influence on the size of the adjustment that is made for the forthcoming promotion. For example, an additional upward adjustment might be made to reflect a relatively high last observation, as it might be viewed as mirroring a recent change in the baseline level of sales (e.g., a recent increase in the popularity of a product). If this observation was well above the forecast for that period (thus leading to a large positive forecast error), its salience, and hence its influence on the adjustment, is likely to be enhanced.

In summary, little is known about the way in which forecasters use the information that they face when producing their judgmental adjustments of statistical baseline forecasts when products are due to be promoted. However, it is an important issue, in that inaccurate demand forecasts can be costly in terms of either surplus inventory or the loss of customer goodwill and sales. It is also important theoretically, in that little research has examined the general problem of which this is an example: the interpretation of diverse information in a time series context. The remainder of this paper investigates whether and how information of different types distracts forecasters from using base rate information efficiently, leading to a decreased accuracy.

3. Methodology and design of Experiment 1

We have adopted a behavioural experimental approach here for testing the hypothesis developed above, while controlling for prior expectations of promotion effects, self-reported knowledge of forecasting and

different types of motivation. Controlled laboratory experiments are being used increasingly to investigate demand forecasting behaviors and related biases (Kremer, Moritz, & Siemsen, 2011; Siemsen, 2011; Harvey & Reimers, 2013; Moritz, Siemsen, & Kremer, 2014), as they allow for systematized examinations of crucial factors that affect the forecasting performance. They are also now common in the operations literature (Gans & Croson, 2008; Croson, Schultz, Siemsen, & Yeo, 2013; Zhao, Zhao, & Wu, 2013).

We report in detail on one experiment (labelled Experiment 1) that was built on the experience gained from a number of preliminary experiments. The responses in these preliminary experiments provided information on features such as screen design and the number of time series that could be used, as we discuss below. The participants in Experiment 1 were management students who were studying for bachelors, masters or doctoral degrees at the Universities of Bath (UK), Bilkent (Turkey), and Lancaster (UK). They had all studied some forecasting. While they did not have the same level of experience as commercial forecasters, they did have at least as much statistical training as many practicing forecasters. The evidence provided by earlier studies, and recently by Kremer et al. (2016), suggests strongly that there are few differences between student participants and practising forecasters in contexts such as that simulated here. We pick up on this issue in a second experiment that involved executives, as is discussed below.

The participants were asked to assume the role of forecasters for a large company that supplies a wide range of products to supermarkets. They were told that their task was to predict the sales of a number of these products that would be subject to a sales promotion. Each participant was given a briefing that described the task, together with base rate information on the average percentage uplift in sales that was achieved by promotions at this supermarket.

Once the experiment had started, other information was provided through an FSS , including a graphical display (see Figure 1 for a typical screenshot) that was designed to have features and a format that were similar to those found in some widely used commercial forecasting systems (e.g. ForecastPro^{TM}). The realism of both the system and the participants' task was intended to enhance the

ecological validity of our experimental task and its findings (Rogers & Soopramanien, 2009), and was based on our earlier field-based research in companies (Goodwin et al., 2007; Fildes et al., 2009). This was considered especially important because many experimental tasks in the extant literature do not allow the assessment of the combinations of factors that apply in practical contexts, and the current task was structured so as to replicate the forecaster's everyday experiences on the job as closely as possible.

Key elements in the design of the task include the length of the sales history presented graphically (24 periods), the number of past sales promotions (here chosen as one, a simplification for promotion-intensive products), the types of products (we aimed for everyday products that would be familiar to participants) and the promotional information. The demand generating process and the forecast function (described below) were also chosen to replicate the types of series and forecasting methods that practicing demand forecasters face; thus, exponential smoothing has been used (for example, all of the companies examined by Fildes et al., 2009, and Alvarado-Valencia, Barrero, Önkal, & Dennerlein, 2017, used this as the basis of their forecasting and adjustment process). The choice of the average uplift may also be important. An analysis of the promotional effects reported by companies provided a wide range of possible average uplifts, with Nakamura, Pechey, Suhrcke, Jebb, and Marteau (2014) estimating a range of 20% to 40% ,while an analysis of US store data gave much higher estimates, with a range of 127% to 519%.[2] These estimates gave us a wide choice, and an early experiment using 80% was contrasted with participants' prior views (which provided a median estimate of 50%). Since this last figure was within the range of plausible uplift values, we chose to use it in the experiments reported here. This average uplift was highlighted both in the cover story and in the information presented on the computer screen during the trial run.

The participants first saw product details for a particular SKU (the SKUs were presented in random order), a corresponding time series sales history of 24 periods, and the corresponding statistical forecasts for all periods, including the 25th.

[2] Thanks are due to Shaohui Ma, who provided these figures as part of research reported by Ma, Fildes, and Huang (2016).

The data were generated according to the rules:

$$Sales_t = BaseLineForecast_t + PromInd_t * Promotional\ \ Effect_t + \varepsilon_t$$
$$BaseLineForecast_t = 0.2 * Sales_{t-1} + 0.8 * BaselineForecast_{t-1} + (Perturbation\ for\ t = 25)$$
$$Promotional\ \ Effect \sim (80,120)$$
$$PromPeriod_t \sim orm(1,24))$$
$$PromInd_t = 1\ when\ t = PromPeriod_t, \ = 0\ otherwise$$
$$\varepsilon_t \sim (0, stddev).$$

The initial *BaselineForecast* was set to 200, with a promotional effect of between 80 and 120 units, so that it was, on average, 50% of the typical sales in non-promotion periods. The past promotional period occurred at a random point over the 24-period history. The standard deviation (*stddev*) had a value of either 40 or 80. On the rare occasions where the simulated observation turned out to be negative, a value of zero was substituted.

The FSS provided a simple exponential smoothing forecast, as shown, apart from a random perturbation in period 25. This was done by assigning each series a value of zero, or ±50*U(0.4,0.6), i.e., a random perturbation of between 20 and 30 in absolute value. This limited the collinearity between the forecast, the previous sales observation and the previous error, thus allowing its influence on the adjustment to be estimated more precisely. It was made clear to the participants that the baseline forecast did not include any promotional effects, as the previous baseline forecast was not updated for promoted periods, *t*. The timing of the single promotion in the historical data was generated uniformly for an integer period between 1 and 24. The timing and effect of this promotion varied across SKUs, with a mean sales uplift of 50% (relative to the baseline forecast).

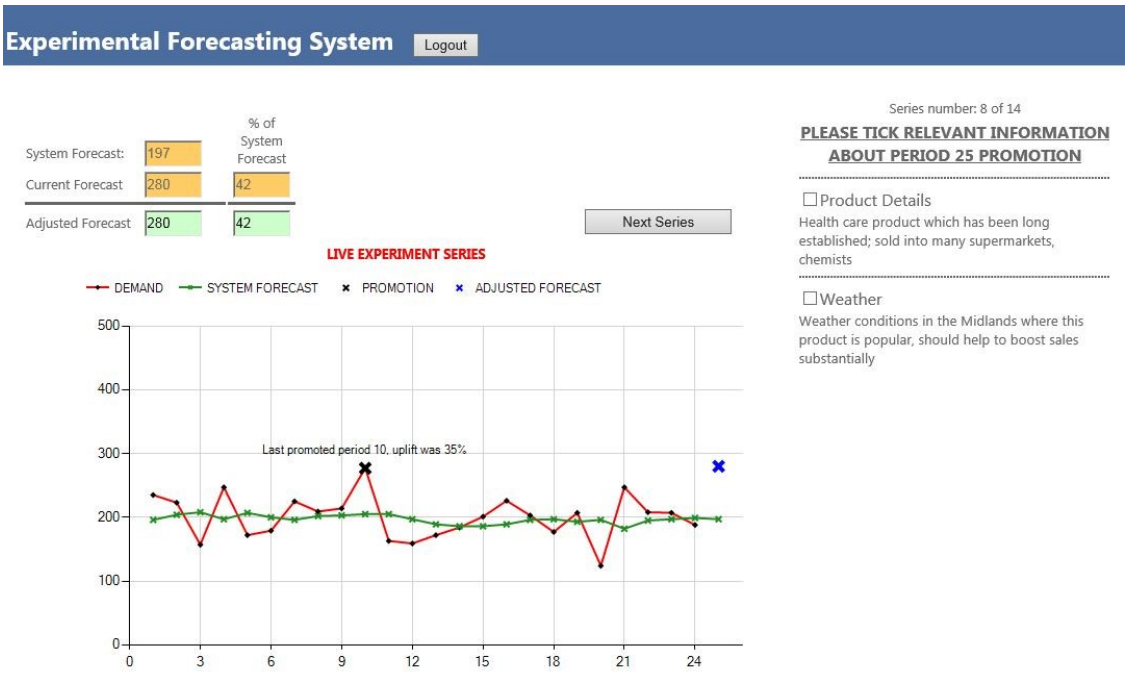


Figure 1. Screenshot of the experimental forecasting support system.

For each SKU, in addition to the historical sales series and statistical forecast, the screen displayed between zero and four written statements which gave reasons as to why the level of sales uplift in the forthcoming promotional effect might be expected to be above or below the average ('positive' and 'negative' reasons). These reasons related to the amount spent on the promotion (e.g., "Over £1m is being spent on the promotion, double the usual size"), market research (e.g., "Focus groups have been quite negative about the promotional packs, but we can't change these at this late stage"), weather factors (e.g., "This product is mainly sold in the North where the weather conditions should be good for high sales according to the latest forecast") and campaign effectiveness (e.g., "We were hoping for a celebrity endorsement of our product as part of the campaign, but negotiations have not been successful and, unfortunately, we will have to run the campaign without this endorsement"), with a total of four reason types. These reasons were tested on nine experts for their plausibility and relevance to promotional events. A full list of the reasons is available from the authors. Half of them were positive and half were negative, with 12 in each category for each of the four reason types. The number of reasons displayed at any one time, the appearance of positive or negative reasons and the order of their display were all

randomized. Finally, having been presented with all of this information, the participants were invited to use their judgment to adjust the baseline forecast for each SKU so as to take into account the forthcoming promotion for that product. These statements, which are typical of the issues that arise in S&OP discussions (see Goodwin et al., 2007), had no impact on the simulated promotional effects. In organizational S&OP, there is typically no evidence of such information having an effect on the impact of promotions (although an exception has been observed in brewing, see Nikolopoulos & Fildes, 2013).

In order to control for the possible moderating effect of motivation, each participant was assigned randomly to one of three treatments that were designed to provide different types of motivation. The first group were told that they would be rewarded when a promotion uplift exceeded 50%; although this was beyond their control, it was thought that the possibility of this reward might lead to a desirability bias. The second group were told that they would be rewarded for the accuracy of their forecasts. Finally, the third (control) group were given a reward merely for participating in the experiment. In the first and second groups, the best two forecasters in each treatment received an Amazon voucher, while a prize draw was used to select the two winners in the control group. This led to a 3 (motivation type) between-subjects × 12 (SKUs) within-subjects design.

Before embarking on the experiment, the participants were asked to indicate their prior view of what a typical percentage sales uplift would be for a fast-moving consumer good that was being promoted. They then made forecasts for the two SKUs that were used as a trial run in order to familiarize themselves with the FSS, before making forecasts for the 12 additional SKUs that formed the basis of the experiment. For each SKU, they had the option of indicating which, if any, of the reasons displayed had led them to make their adjustment. During the trial run, they were provided with an assessment of why the earlier promotion had or had not been a success, though no empirical evidence was produced to support the assessment. They also received overall feedback on their accuracy after making forecasts for both trial-run SKUs. No feedback was provided in the main part of the experiment. At the end of the experiment, each participant completed a questionnaire that was designed to assess their knowledge of

forecasting, their engagement in the task, their expectations regarding the accuracy of their judgmental adjustments, and their interpretation of the reasons that were provided.

Because of the complexity of designing experiments that provide a realistic simulation of the supply-chain forecaster's task, a number of preliminary experiments were run, involving over 200 participants. These enabled us to fine-tune the design and the screen display, in order to eliminate potential confounding factors and identify the key issues that merited further investigation. These variations included using different numbers of series, providing fixed numbers of reasons, forcing participants to select both primary and secondary reasons to support their adjustments, having an average promotional uplift of 80%, and including a trend in the data. The results of these experiments were consistent with those that we discuss next, suggesting that our results are robust. Thus, these earlier results will not be reported here for the sake of brevity, but are available from the authors.

4. Analysis and results of Experiment 1

The experiment involved 126 participants. We then excluded respondents who made only the very smallest average adjustments (i.e., their mean adjustment was less than zero), as this suggests either a limited understanding of promotional effects in retailing or no engagement with the experiments. Thus, the results are based on a sample of 112 participants. As was indicated above, the participants also responded to a post-experimental questionnaire. The main results of interest are summarized in Table 1.

Table 1 Questionnaire responses.

Question	Mean	Std.Dev.
Rating of overall knowledge of demand forecasting	2.77	0.86
Expectations of statistical forecast performance	3.03	0.77
The reasons provided had a direct influence on my forecasts	3.46	1.07
Confidence in my final adjusted forecast	2.66	0.94

Motivation to engage with the task	3.40	0.98

Scale: (1) none / low expectations, to (5) high / high expectations (depending on the question).

The results show that the participants were generally motivated by the experiment and responded to the reasons provided. In general, they did not 'write-off' the potential performance of the statistical baseline forecasts, despite the fact that they were bound to have large errors in a promotion period. This may reflect some acknowledgment of the usefulness of the statistical forecasts in establishing a reliable baseline for judgmental adjustment. The participants also indicated a lack of confidence in the accuracy of their adjusted forecasts, which is reasonable given the level of uncertainty that is associated with such promotion effects.

We conducted a preliminary data analysis prior to developing a full linear model, to explain the size of the participants' adjustments. The participants' median prior estimate of the percentage uplift achieved in supermarket promotions was 50%. However, their median estimated uplift during the experiment was only 30%, which is significantly lower ($p < 0.001$) than the base rate of 50%, a result that is consistent with a neglect of the base rate. This provides support for both H1 and H2. The distribution of these percentage adjustments was broadly normal, with a few positive outliers. Only 25% of the adjustments were greater than the base rate of 50%. However, some were as high as 200%, which is quite possible for the sorts of products that were included in our experimental design.

4.1. Statistical modelling

Statistical modelling was used to identify the factors that helped to determine the sizes of participants' adjustments, and in particular, whether the previous promotion effect and reasons were distracting them from the base rate. This also enabled us to estimate the extent of any distraction, after taking into account the potential moderating factors discussed in Section 2.2. The nature of the experiment, where each respondent is given a sequence of series in random order, together with random information cues, requires

a more sophisticated analysis than a standard ANOVA or regression. Individual participants can be expected to have random responses to both the series and the cues. The advantages of using linear mixed effects models for this situation (Verbeke & Molenberghs, 2000) have been summarized as that "they allow the researcher to simultaneously consider all factors that potentially contribute to the understanding of the structure of the data….including standard fixed effects ….. and covariates" compared to standard approaches (Baayen, Davidson, & Bates, 2008). The statistical model is as follows:

$$\mathbf{Y}_i = X_i\boldsymbol{\beta} + Z_i\mathbf{b}_i + \boldsymbol{\varepsilon}_\mathbf{i}$$
$$\mathbf{b}_i \square \quad ,$$
$$\boldsymbol{\varepsilon}_\mathbf{i} \square \quad)$$

where $\mathbf{Y}_i$ **is** the n_i dimensional response vector for respondent i, representing the promotional estimates for the jth series. X_i and Z_i are the $n_i \times p$ and $n_i \times q$ dimensional matrices of the factors that influence the response, while $\boldsymbol{\beta}$ is the p-dimensional vector of fixed treatment effects and $\mathbf{b_i}$ is the q-dimensional vector of random effects. The covariance matrices are potentially important to the model building. **D** and **Σ** are assumed to be independent. A repeated measures design is needed because the observations of the promotional uplift estimates from a given subject cannot be assumed to be independent of each other; for example, in the sequence in which they were made. The standard assumption that is made for the variance-covariance matrix of the random effects, **D**, is that the respective variances of the $\mathbf{b_i}$ differ from each other but are independent of each other; this is called the variance component assumption. In addition, the sensitivity of the estimated effects to changes in this assumption has been tested through an assumed autoregressive structure in order to capture any carry-over effect between the repeated observations, i.e., an AR(1) structure was assumed for **D**. SAS 9.3 has been used to estimate the equations using a restricted maximum likelihood.

The key features of the linear mixed effects model are set out below:

- The dependent variable is the adjustment percentage transformed into log (1 + *Proportional_uplift*) to ensure better error distributional characteristics (Davydenko & Fildes, 2013).

- The effects of variables relating to the past forecast history were assumed to be random effects, as they depend on the individual participant. These variables were: the log of the respondent's prior estimates of promotional effects, the log of the last forecast percentage error (measured as log(*Forecast/Actual*)), the log of the uplift achieved in the last promotion (i.e., actual promoted sales over the baseline forecast), the log of the latest forecast for the promoted period, and the timing of the previous promotion.
- The effect of the series noise variance was treated as a fixed effects class variable.
- Participants' responses to the information cues were treated as random effects specific to the individuals.
- The numbers of positive and negative reasons were treated as fixed effects class variables, i.e., treatments.

Formally, let Y_{ij}= log (1+*Proportional_uplift*), the uplift estimated by the *i*th participant for the *j*th series. Then, the model being estimated is

$$Y_{ij} = \beta_0 + \beta_{1i} * \ln(Last\_promotional\_uplift)_j + \beta_{2i} * \ln(Last\_Actual)_j + \beta_{3i} * \ln(Current\_Stat\_forecast)_j + \beta_{4i} * \ln(\Pr ior)_i + \lambda Noise_j + \beta_{5i} * (Timing\_past\_promotion_j) + \gamma_i Reasncat_{ij} + error_{ij}$$

,

where $\beta_1,\ldots \beta_4$, are random effects, *Noise* is treated as fixed, and *Reasncat* is treated as random. *Reasncat* is defined as the number of positive reasons minus the number of negative reasons. In addition, the results presented have points of high leverage removed, where leverage was measured using Cook's *D* (eliminating points with $D > 0.002$ – approximating one of the recommended cut-offs of $4/n$). Various modelling choices also needed to be resolved, and in particular, how to characterize the numbers of negative and positive reasons. On a methodological note, we sought to test the robustness of our chosen approach by examining alternatives, since there is no 'optimal' route to establishing a model. Several alternatives were considered, including using both variables (with an interaction) and one variable together with the difference between the numbers of positive and negative reasons. Using the variable *Reasncat* (the number of positive reasons minus the number of negative reasons, as defined above) proved

the most parsimonious specification, with the minimum BIC. In addition, various interactions were also included, but did not add any explanatory power. Any non-linear effect of timing was also checked, but a linear model proved adequate. A sensitivity check on the assumption of the correlation structure of the repeated measures did not show any substantive differences.

4.2. Results of modelling

The results from the model are shown in Table 2, which, as stated earlier, excludes observations with high leverages. However, as a check on the robustness of our findings, the results from estimating the model with the full set of observations remained broadly the same (1560 observations were reduced to 1309 after excluding high leverage points and non-compliant responders). The parameter coefficients are interpreted as percentage effects, meaning that, for example, having four negative reasons and no positive reasons (*Reasncat* = –4) lowers the average adjustment by 10.1% (= 100[1 – exp(–0.1067)]). It can be seen that both the previous promotion uplift and the reasons were associated significantly with the adjustments made by the participants, which is consistent with H1. Higher uplifts in the previous promotion were associated with higher adjustments. This effect was slightly greater for more recent promotions. As expected, lower levels of noise were also associated with higher estimated uplifts, suggesting that high noise was making the effects of the previous promotion less salient. The significant negative coefficient for the statistical baseline forecast is consistent with participants placing their estimate of the uplifted sales between the baseline forecast and the previous promotion. This would account for the tendency to underestimate the expected uplift of 50%.

Table 2. Model of the adjustment: dependent variable is $\log_e(1 + \textit{Proportional\_uplift})$.

Effect	**Estimate**	***p*-value†**
Intercept	0.505	<0.0001
ln(last promotion uplift)	0.275	<0.0001
ln (last actual)	0.037	0.001
ln (last stats forecast error)	0.040	0.105

ln(current stats forecast)	–0.128	<0.0001
ln(Prior)	0.035	0.014
Low noise	0.021	0.018
Timing of past promotion	0.001	0.036
Reasncat = –4	–0.107	<0.0001
Reasncat = –3	–0.136	<0.0001
Reasncat = –2	–0.114	<0.0001
Reasncat = –1	–0.077	<0.0001
Reasncat = 0	–0.078	<0.0001
Reasncat = 1	–0.052	0.001
Reasncat = 2	–0.023	0.112
Reasncat = 3	–0.027	0.100

Notes: Available n = 1560; sample size after deleting high leverage points = 1309. *Reasncat* = No. of positive reasons supplied – No. of negative reasons.
† All tests are one-sided apart from that for low noise (and intercept).

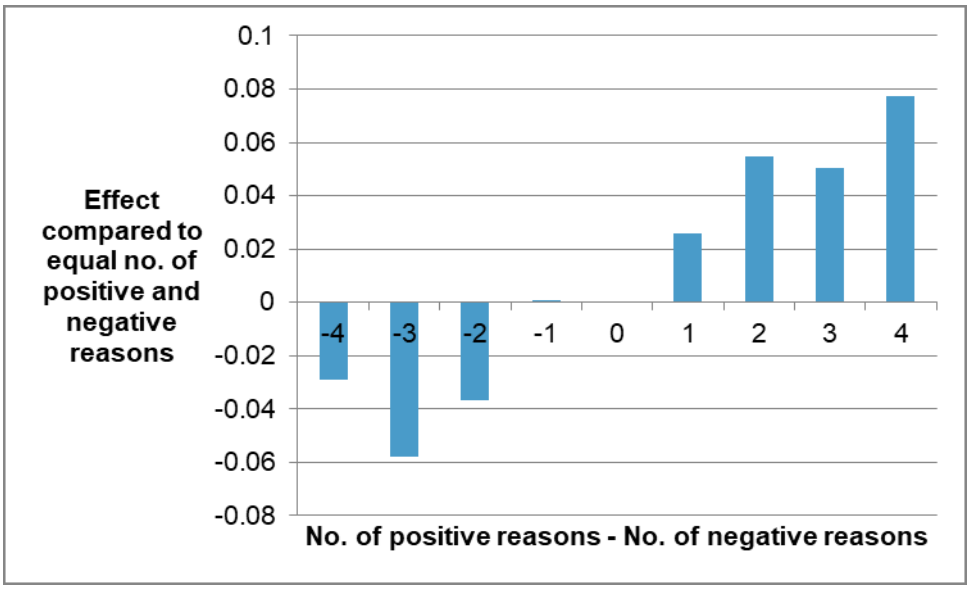
Figure 2 shows the relationship between $\log_e(1+Proportional\_uplift)$ and the difference between the numbers of positive and negative reasons. The effects are compared with situations where there are equal numbers of positive and negative reasons. It can be seen that, in general, the greater the number of positive reasons relative to the number of negative, the larger the upward adjustment. This suggests that the participants were balancing the reasons against each other, indicating that they were using a compensatory strategy. Broadly speaking, the greater the balance of reasons in one direction, the greater the distraction from the base rate, despite the unknown diagnosticity of these reasons, a result that is consistent with H1.

Did negative reasons have a greater influence than positive reasons? An analysis of 'contrasts' showed that one more positive reason has a greater impact than one more negative reason, but there is little difference between having two more positive and two more negative reasons. Overall, the results suggest that positive reasons have a slightly greater effect than negative ones. This supports the argument that the propensity to underestimate the promotion effects is a result of the tendency to place the adjusted forecast between the baseline forecast and the previous promotion, rather than the alternative of a greater weight being attached to negative reasons.

We investigated whether any of a number of additional variables had a moderating effect on the results. Table 2 shows that participants who came to the experiment with higher prior expectations of promotion uplifts tended to make larger upwards adjustments to the baseline forecasts. However, the carry-over effect of this to their individual SKU adjustments was small (as shown by the coefficient of the ln(*Prior*)). There was also an apparent country effect between the participants based in the UK and Turkey ($p < 0.001$), with the latter providing lower forecasts of uplifts. Once individual priors were included, the effect was insignificant. This probably reflects the different retail environments that the participants were familiar with. In addition, Table 2 shows that the adjustments tended to be larger when the most recent actual sales figure was higher (this always turned out to be a non-promotion period). As has been discussed, a high recent sales figure might be interpreted as a signal that the underlying level of sales has increased, so that a greater adjustment to the statistical forecast is needed.

Figure 2. Effects on respondents' estimates of the uplift of differences between the numbers of positive and negative reasons.

Note: The effects are measured relative to situations where there are equal numbers of positive and negative reasons. The dependent variable is $\log_e(1+Proportional\_uplift)$.



There were no other substantive or significant effects on the size of the adjustment in regard to either the different motivation treatments or the characteristics of the participants, such as their knowledge of statistical forecasting, apart from the finding that participants' motivation in the task proved significant in increasing their average uplift. Telling participants that they would be rewarded if the uplift exceeded 50% (in an attempt to induce desirability bias) had no significant effect, nor did rewarding accuracy.

4.3 Discussion of Experiment 1

Overall, the results of Experiment 1 suggest that, when making their forecasts, participants were distracted from the 50% base rate by the previous promotion uplift and by the reasons given, despite this information having either no or unknown diagnosticity. In particular, they appeared to set their adjustment to be between the baseline statistical forecast and the previous promotion, resulting in a tendency to under-forecast the forthcoming promotion effect. These findings are consistent with earlier results on base rate neglect, which suggest that base rates are eclipsed by more salient information with a potentially lower predictive value. In fact, the introduction of any reasons surrounding the promotion had a negative effect on the calibration of the adjustment, a result that we establish by comparing situations in which no

reasons were offered with those in which positive and negative reasons counterbalanced each other. It appears that the availability of any reasons will distract forecasters from the base rate. Our findings also replicate studies that show that managers introduce variation into a system even when they know that the demand is constant, as our participants did when they departed from the 50% uplift (Sterman & Dogan, 2015).

None of our motivation treatments, which were intended to control for possible motivational effects, had a significant effect on the size of the adjustments. The absence of a desirability bias for those who were rewarded for higher than average uplifts was perhaps surprising, and once again demonstrates that it is difficult to replicate motivational and the associated political effects that occur in the field in the laboratory. A small reward of a voucher for higher or more accurate sales forecasts is not the same as the incentive to please the boss with a high forecast or the incentive to bring prestige and resources to one's department by producing reliable forecasts.

5. Experiment 2

In Experiment 1, the participants had access to both sorts of potentially distracting information cues, namely the previous promotion uplift and the reasons. This did not allow the effects of information with zero diagnosticity and information with unknown diagnosticity to be examined separately. Experiment 2 had a simpler design. Participants were assigned randomly to one of two treatments. In the 'previous promotion' treatment, the series contained sales obtained in a previous promotion, but no reasons relating to the forthcoming promotion were displayed. In the 'reasons' treatment, reasons for the success or otherwise of the forthcoming promotion were displayed, but no previous promotion effects appeared in the time series. In this case, two negative reasons, two positive reasons or zero reasons were displayed for each SKU, with the number of reasons being selected at random. The design was based on the results of the previous experiment, where the influential variable proved to be the difference between the number of positive reasons offered and the number of negative reasons. The effects proved to be approximately linear, between –2 and 2 reasons. In the 'reasons' treatment, the promotion always

appeared in period 18, thus eliminating any possible timing effects. Unlike Experiment 1, there was no random perturbation of the statistical baseline forecast and no motivation treatments were included. Each participant made forecasts for period 25 for 14 series, including two trial series. In all other respects, the experiment was the same as Experiment 1.

The participants were 30 executives who were undertaking an Executive MBA module on forecasting, so the experiment also enabled us to test whether the effects observed in Experiment 1 were also valid for experienced executives.

5.1. Results of Experiment 2

While the two sets of cues, past promotions and reasons, can be embedded in a single analytical model, our analysis shows that there are interaction effects that annul any efficiency gains in the estimation of coefficients. Hence, separate mixed linear effects models were estimated for the adjustments made by participants in the two treatments. The overall mean (median) adjustment made was 49.4% (39.8%). The models had the same underlying structure as that used to analyse Experiment 1, except that the number of positive reasons minus the number of negative reasons was represented by a single variable rather than a series of dummy variables, reflecting the approximately linear relationship referred to above. As before, the dependent variable was $\log_e(1 + \textit{Proportional\_uplift})$ and high leverage points were removed. This time, ln(*last actual*) and ln(*last stats forecast error*) were not included in the list of independent variables, because the lack of random perturbation in the statistical forecast meant that they would be collinear with that forecast.

The results from the group of executives taking part in this experiment generally support those reported for the earlier experiment. As Table 3 showed, for the 'previous promotion' group, the previous promotion had a highly significant effect on the estimated uplift for the forthcoming promotion. Also, as in Experiment 1, a lower level of noise led to higher estimated uplifts, which is consistent with the notion that the effect of the previous promotion was less salient under conditions of high noise. However, unlike

Experiment 1, a higher statistical forecast was associated with a larger upward adjustment, probably due to multicollinearity with the last actual (which was broken in Experiment 1). The effect of these factors was that the overall adjustment had a (trimmed) mean of 43% and a median of 40% (which is not significantly different from 50%, but is substantially and significantly less than the observed means of the past promotions, 57.5%).

Table 3 shows that participants in the 'reasons' group were influenced significantly by the reasons provided when they estimated the promotion uplift. The greater the balance in favour of positive reasons, the greater the upwards adjustment that they tended to make. For this group, the mean estimate when no reasons were provided was 52% (close to the base rate), although the median estimate was only 43%. As with the 'previous promotion' group, higher statistical forecasts were associated with larger upward adjustments, but this more experienced group was fixed more firmly on their prior promotional estimates. However, as expected, the level of noise did not have a significant effect, as there was no previous promotion uplift to be submerged in high noise.

Table 3 Model of promotional adjustment for the two treatments: 'Previous promotion' and 'Reasons'.

	Treatment 1: Previous promotion		Treatment 2: Reasons	
Effect	**Estimate (n = 159)**	***p*-value**	**Estimate (n = 161)**	***p*-value**
Intercept	–4.830	<0.001	–2.946	0.001
ln(last promotion uplift)	0.678	<0.001	n/a	n/a
ln(current stats forecast)	0.889	0.001	0.598	0.003
ln(Prior)	0.418	0.153	1.160	0.133
Low noise	0.190	0.001	–0.022	0.608
No. of positive reasons minus no. of negative reasons	n/a	n/a	0.032	0.0416
Mean adjustment	51.9		46.6	
Median adjustment	42.9		33.8	

Note: All tests are one-sided except for those for low noise and the intercept.

In conclusion, Experiment 2 clearly demonstrated that, when the information cues were presented separately, both past promotions with zero diagnosticity and qualitative information with unknown diagnosticity distracted participants' estimates of promotional adjustments from the normative adjustment of 50%. This provides further support for H1. Also, the effects observed earlier with a diverse group of business students have been replicated with experienced executives. However, the support for H2 (concerning the effects of information on under-adjustment) was weaker, with the mean and median adjustments being closer to 50% than in Experiment 1, though they were still generally below this figure. This may be because each group in the experiment had only one main source of potential distraction (either the previous promotion or the reasons). The lower average adjustments for the 'reasons' group may reflect a tendency to anchor on the baseline forecast, and the fact that this group did not observe a previous promotion that might have 'pulled' their estimates away from the anchor.

6. General discussion and conclusions

The efficient use of information by demand forecasters can be crucial, given the negative effects of forecast errors on production, distribution and inventory planning. For example, Kremer et al. (2016) estimate that a given percentage improvement in accuracy translates into a similar percentage reduction in safety stock. Given their repercussions for the supply chain, promotions pose particularly strong challenges to S&OP decision-makers. The results of this experiment-based study suggest that the provision of information relating to promotions can be detrimental to the forecast accuracy when it has either no or unknown diagnosticity, in spite of its salience. This finding has important implications for both the design of the forecasting support systems that are used commonly in supply-chain-based organizations and the extent to which supply chains can operate efficiently. The systems typically emphasise the provision of information to the forecaster in an amenable and accessible format, irrespective of its predictive value. However, our results suggest that these 'passive' systems may be

inimical to accuracy. In particular, the participants appeared to adopt a version of the 'last-lift' heuristic, the most common promotional forecasting method used in practice. Their mistake was to ignore the average uplift, focusing instead on the last observed value.

Both facets of the participants' sub-optimal forecasting suggest that FSSs need to be redesigned. Systems that actively evaluate and filter information before presenting it may lead to improvements in accuracy. Parikh, Fazlollahi, and Verma (2001) found that FSSs which provided informative guidance, which they defined as the provision of unbiased, relevant information without a specific suggestion, were superior in promoting learning relative to systems that suggested how the information should be used. However, the emphasis needs to be on the provision of diagnostic and salient information. For example, in promotion forecasting, a laboratory study found a system that identifies analogous past promotions and provides estimates of their average effects to improve the forecast accuracy (Lee, Goodwin, Fildes, Nikolopoulos, & Lawrence, 2007). However, as Lim and O'Connor (1995) and now Dietvorst, Simmons, and Massey (2015) have shown, changing forecasters' habit of misweighting information remains difficult. Such intentional and unintentional misuses of information, and the prevalence of habitual (mis)weighting schemes, further support the call for an effective redesign of FSSs in order to aid predictive performance. However, redesigning the organization's FSS alone is not sufficient, as the S&OP process also impacts information sharing and the salience of individual pieces of information that are thought to be relevant but are of unknown diagnosticity. As a consequence, the FSS and the S&OP process need to be considered together, incorporating some of the ideas laid out by Oliva and Watson (2009). The research question that this raises is whether an S&OP process that incorporates an analytical 'notes' system into the supporting FSS and attempts to summarize past promotions (perhaps via short stories that include explanations of the available information and reasons for selecting a particular forecasting model(s)) could be effective. In addition, the influence of prior beliefs about the effectiveness of promotions merits further attention. The psychological research on conservatism indicates that such beliefs can be difficult to change in some circumstances, despite the provision of base rate information (Hilbert, 2012). However, Gaeth and Shanteau (1984) suggest that training may help, and there is some

support for the idea that more experienced forecasters, like the auditors considered by Shelton (1999), may be less prone to strong responses to irrelevant qualitative information (as may have been the case in our second experiment).

Is the underestimation of promotion effects that we found in our laboratory experiments typical of what happens in the field? The evidence is sparse. Our study suggests that the bias is a result of the poor design of the FSS, but no field study has provided details of either the characteristics of the specific FSS that was used in promotion forecasting or the role it played, if one was used at all. Some field studies have reported that judgmental adjustments tend to suffer from an optimism bias (Fildes et al., 2009; Franses & Legerstee, 2011), but Müller (2011) reached the opposite conclusion. However, these studies focused on adjustment behaviours in all periods, rather than specifically in promotion periods. Further work on the forecasting of promotional events is clearly needed in order to disentangle the confounding factors, including the effects of a promotion forecast.

An obvious question is: how were the participants expected to know that the information that they were presented with had either no or unknown diagnosticity? However, a deeper reflection reveals that the diagnosticity of the information was self-evident. A sample of just one previous promotion, when the promotion effects are subject to unknown levels of variation and the average promotional uplift is known, clearly lacks diagnosticity. The presentation of reasons, such as, “In this campaign, we will outspend our competitors by 100%”, without any supporting information on the typical effect of this factor on the number of units sold, means that the reasons self-evidently had an unknown diagnosticity. While the failure of participants to discount the extraneous information may not have been a surprise, our model has enabled us to measure the degree to which different types of such information impact judgmental forecasts in a realistic situation. The evidence that we present shows that the range of information that is taken into account is wide, and damaging to the accuracy.

However, like most experimental studies, this work has limitations. One issue is that the participants may have felt obliged to deviate from the 50% base rate, otherwise why were they being invited to take part in the experiment? Simply entering a 50% uplift for every SKU may have seemed too easy, or may

have been perceived as signaling disengagement from the forecasting task. In this respect, though, the experiment was an accurate reflection of the field. For example, Fildes et al. (2009) found that forecasters in companies tended to make lots of unjustified adjustments to statistical forecasts. There is evidence that forecasting staff often make these adjustments in order to signal that they care about the forecasts produced, to display a sense of ownership of the forecasts, or simply to justify their organizational roles (Önkal & Gönül, 2005). Having information that provides an apparent rationale for such adjustments is likely to increase their prevalence.

The participation of students in Experiment 1 may be regarded as another limitation, despite their motivation and knowledge of forecasting. However, this is unlikely to affect the substantive conclusions, as Experiment 2 indicated (see also Kremer et al., 2016). In addition, while the on-screen simulation mirrored the operational realities of forecasting closely, the demand model and the promotional effects were based on a simple statistical model. The results may also depend on the features of the baseline statistical model, where the smoothing parameter is known to affect responses (Kremer et al., 2011). Building on the results presented here, when much of the information available to the forecaster has no diagnosticity, it would be useful for future research to examine the behaviors of forecasters when the statistical model captures some promotional drivers. A second issue is whether the different types of information examined here (or observed in the S&OP process) are interpreted differently and given different weights when adjustments are made. A limited investigation supports this view.

In summary, there appears to be substantial scope for design innovations in forecasting systems, given the limitations of the current systems (Fildes, Goodwin, & Lawrence, 2006). These may include structured support for the filtering and integration of qualitative and quantitative information, targeted to individual forecasters, as well as support in the design of collaborative forecasting systems that reach across different supply chain partners operating under diverse information platforms. These suggestions have implications for the organizational design of the S&OP process, and further work on such innovations promises to enhance the communication between forecasters and decision makers, with an extensive impact on the supply chain performance overall.

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